Estimating potential soil erosion for environmental services in a sugarcane growing area using multisource remote sensing data

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ABSTRACT

Characterization of landscapes is crucial in modelling potential soil erosion to ascertain environmental services that are provided by the main land use in the ecosystem. Remote sensing techniques have proved successful in characterization of landscapes. In this study area of a rain-fed Kibos-Miwani sugar zone of Kenya, we used Normalized Difference Vegetation Index (NDVI) data extracted from satellite imagery to characterize the spatial and temporal heterogeneity of the vegetation conditions, and to model potential soil erosion. Data used included Moderate Resolution Imaging Spectroradiometer (MODIS) 250 m NDVI acquired in the period 2000 to 2012; 30 m Landsat5 time series images acquired between November 2010 and June 2011; a 30 m digital elevation model (DEM); and ground observations (land cover and soil characteristics). Ground observations were cross tabulated and analysed under ISO 17025 laboratory procedures. Temporal NDVI was extracted directly from MODIS 250 m images to study the changes in seasonal vegetation at the region scale, while spatial NDVI was extracted by analysing Landsat 5 images at the field scale. NDVI extracted from Landsat images for a specific date, represented vegetation conditions for that simulation period. To compute potential soil erosion, we ran three simulations using the spatially explicit Fuzzy-based dynamic soil erosion model (FuDSEM) based on identified vegetative conditions, thanks to MODIS data. Input datasets included Landsat 5 NDVI, the slope, aspect, curvature and soil physical properties. Results of land cover presented sugarcane as the main land use, occupying 76% of the land scape. Results of NDVI analysis were consistent with crop management practices, illustrating a spatially heterogeneous land scape with varied vegetation conditions throughout the year. Results of the simulations were not significantly different for the different periods of the year. Out of simulations, we noted a homogeneous low erosion risk in areas with natural land cover with a global mean of 0.42. Medium to intense erosion risk in cropped areas was evident, with erosion risk varying from one pixel to the other. Simulation results suggest that crop management practices (planting and harvesting processes) are the drivers of erosion in sugar cane cultivated areas.

Keywords: Sugarcane, Environmental service, Remote sensing, Land cover, Slope, Soil erosion, Cropping practices

1. INTRODUCTION

Characterization of landscape heterogeneity is crucial in estimation of potential soil erosion from which environmental services that are provided by main land uses to the ecosystem are ascertained [1]. This is because soil erosion is envisaged as a threat towards sustainable land management. Estimation of soil erosion is therefore useful in prevention of soil and nutrient loss [2] for a sustainable productivity of any ecosystem. Soils fundamentally contribute to primary production, through the supply and recycling of nutrients and water to plants and microorganisms in terrestrial ecosystems as well as in agricultural production [3]. Pressure on these soils through agricultural activities and rainfall, introduce degradation at varied scales in time and space, depending on the topography, soil characteristics and crop management practices in the watershed. Land degradation was seen as a critical phenomenon to natural resources [1] in the 21st century [4] as an element of soil erosion. Human induced activities on soil in Africa [5] have subjected soils to vulnerability of erosion. Tropical regions are most vulnerable due to rainy climate, fragile soils [6] and improper land uses [7; 8].

In Kenya, Nyando sugar belt contributes one third of Kenya's sugar demand. In this area, a mosaic of subsistence, sugarcane farming and natural vegetation is found in the escarpment foot. This zone is characterized with multiple planting and harvesting dates for sugarcane crop [9]. Data on land use shows close to 80% of the landscape under sugarcane drawing our interest in investigating its impact of soil erosion. Sugarcane management systems (planting, harvesting) affect soil conditions which have a direct impact on soil erosion. Further, [10] adds that sugarcane crop and its residues reduce the rate of soil erosion. Whereas disadvantages of soil erosion have been documented, there is little etiquette in evaluating soil degradation characteristics. Knowledge on impact of sugarcane cultivation on soil degradation is critical in undertaking effective soil conservation for sustainable management of Kibos-Miwani ecosystem [11]. The objective of this paper is to investigate the soil erosion control service offered by sugarcane farming in Kisumu-Kibos sugar zone using remote sensing data and an erosion model. The study will focus on sensitivity of erosion risk to the vegetation conditions at landscape scale. Different types of remote sensing data are used to qualify the spatial and temporal variability of the agro environmental conditions.

2. BACKGROUND ON SOIL EROSION AND REMOTE SENSING

2.1 Soil erosion models

[2] described soil erosion models as important tools for management of built up, natural and agricultural landscapes. Most soil erosion models simulate erosion processes continuously to obtain solutions in the absence of temporally dynamic information [12]. Results from such models depended on the number of times that the iterations were run, high accuracy being associated with many iterations and this made results subjective. Moreover, when estimating soil erosion over heterogeneous areas, most models are limited [13] due to insufficient spatio-temporal information. In the recent past, spatially dynamic models have been used in computation of potential soil erosion in order to recommend appropriate conservation measures for enhanced agricultural productivity [2]. Modelling potential soil erosion in heterogeneous landscape patterns such as in Kibos-Miwani require a model that is applicable at landscape scale [14] to facilitate recommendations on soil conservation measures that minimize impacts of erosion in a specific environment. Fuzzy logic is important in simulating complex environments since it is capable of processing uncertain data from complex spatial processes [2; 15; 16]. The fuzzy based dynamic soil erosion model (FuDSEM) [2] was developed to simulate landscape processes at catchment scale for enhanced decision making. This is because the Geographic Information System (GIS) based fuzzy models have the advantage of being used in managing uncertainties commonly associated with spatial databases [17]. Additionally, fuzzy models are spatially explicit in nature, integrating temporal information from remote sensing with GIS data to present decision support information for ecological modelling in a GIS environment [18].

2.2 Role of remote sensing in soil erosion modeling

Remote sensing techniques have proved successful in characterization of heterogeneous landscapes when integrated with spatial dynamic models and expert knowledge to investigate the extent of soil losses in agricultural landscapes [14; 2]. In the recent past, information from remote sensing imagery was integrated with spatial data to increase accuracy in monitoring changes in land use [19]. Additionally, [9] recommended the use of satellite images, to provide temporal information on changes in environmental variables in space and time. In the Kenyan scenario where 85% of sugarcane is grown among other land uses with multiple planting and harvesting crop dates [9] time series normalized difference vegetation index (NDVI) from satellite imagery of such landscape facilitated understanding of the vegetation seasonal variations and delineation of fields boundaries.

Recent studies have used NDVI to identify changes in vegetation cover that are presumed to have resulted from crop management practices. The image acquired on a specific date was presumed to reflect results of crop management practices as impacted by environmental variables for that particular space in time [2; 20; 21]. On the other hand, temporal NDVI captures the different stages of land cover from temporal series when integrated with ground data and expert knowledge. This integration provides spatial and temporal information that is critical in the FuDSEM [2] model to quantify potential soil erosion over a heterogeneous landscape [2], and investigate their impact on soil erosion control in space and time.

3. MATERIALS AND METHODS

3.1 Study Area

Kibos-Miwani sugar zone (Figure 1) is located within the Nyando sugar belt between 34.8° E to 35.08° E and 0.002° S to 0.11° S. It stretches from the Kano plains with an altitude of 1000 m to 1800 m in the escarpment. The slope rises from 2% in the plains to >20% in the hilly areas. It is located within the sub humid agro-ecological zone receiving rainfall of between 1400 mm and 1550 mm. The main crop in the zone is sugarcane, besides maize and horticultural crops. Sugarcane is planted in the months of April and September in accordance with the bimodal rainfall in February to June and September to December. Soils of the plain land are dominantly black cotton cambisols that easily clog with increased rainfall and crack during prolonged drought with temperatures rising to 33° C. The highlands are dominantly well drained sandy loamy acrisols. It is the spatially heterogeneous terrain, diversified cropping systems, varied soil types and rainfall in this zone that provide an enabling environment for evaluation of a soil service offered by sugarcane crop to the ecosystem.

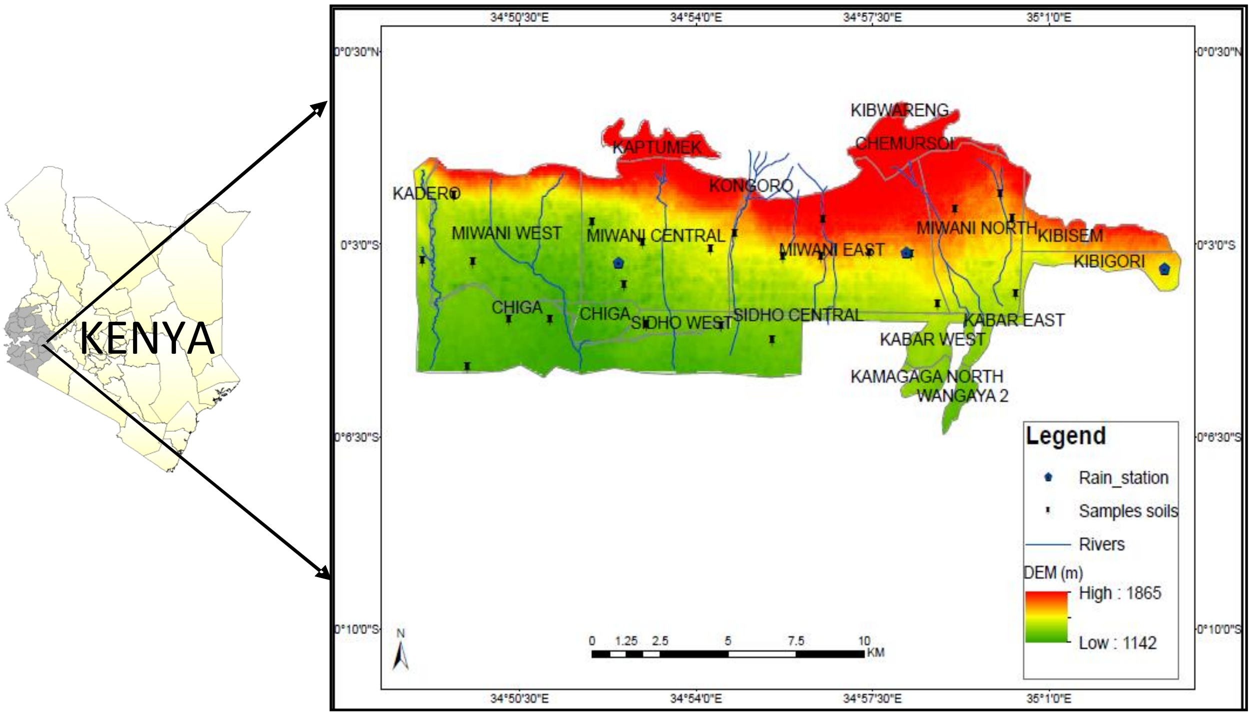

Figure 1. Location map of Kibos-Miwani sugar zone overlaid on a 30 m digital elevation model (source: ASTER).

3.2 Data

3.2.1 Image Data

Two types of satellite images with different spatial and temporal resolutions were used in this study to explore spatial and temporal variability in the landscape. A set of eight 30 m Landsat5 time series images was acquired between November 2010 and June 2011 from the USGS website; the images were processed for Normalized Difference Vegetation Index (NDVI) to provide information on vegetation conditions as impacted by crop management practices during a specific period. Furthermore, 16-day Moderate Resolution Imaging Spectroradiometer (MODIS) 250 m NDVI images for the period 2000-2012 was downloaded from the USGS website to evaluate seasonal variation of the vegetation conditions in the study area.

3.2.2 Digital Elevation Model

30 m ASTER Digital Elevation Model (DEM) was downloaded from the United States Geological Survey (USGS) website (Figure 1). The DEM was processed using the spatial analyst tool in a geographical information system (GIS) to compute the slope, curvature and aspect, of the study area.

3.2.3 Soil Characteristics

A stratified random sample of soils from 24 locations in this zone was collected in August 2012 (Figure 1) for analysis of texture, bulk density, hydraulic conductivity and soil moisture content based on accessibility and soil type. During sampling, we took cognisance of variability in soil types present in the area, in relation to slope and distance to the escarpment. These samples were collected using stainless steel cans at 30 cm and 60 cm depths and mechanically analysed at KESREF using ISO 17025 laboratory procedures.

3.2.3 Ground Survey Data

Through a participatory approach, 200 farmers were interviewed individually in August 2012 through a stratified sampling approach. Farmers provided the following datasets through a questionnaire: i) land cover type, ii) crops grown yearly, and iii) planting and harvesting periods. Samples of natural vegetation (shrubs, fallow, and pasture land) found close to interviewed farmers were also encoded.

3.2.4 Rainfall data

Monthly rainfall data for Kibos-Miwani sugar zone was measured using three rain gauges for the period 2001-2012, from three locations distributed within the sugar zone (Figure 1). This eleven year data was cross tabulated for the monthly annual mean.

3.2.5 Erosion model data

The Fuzzy-based dynamic soil erosion model (FuDSEM) [2] was used in this study. FuDSEM has the advantage of being spatially explicit and temporally dynamic compared to other models [2; 22]. It is composed of 4 modules: i) potential soil humidity; ii) Potential sliding; iii) transport capacity, and iv) potential soil erosion (Figure 2). Potential soil humidity varies in time and space depending on humidity index, field capacity and the aspect of the landscape. Potential superficial sliding of the given space depends on potential soil humidity, hydraulic conductivity, precipitation received, and NDVI (vegetation conditions). Transport capacity depends on potential superficial sliding, the slope and curvature of the landscape. Lastly, potential soil erosion depends on transport capacity, bulk density and porosity.

Based on fuzzy logic, the membership score for all model data was calculated using the MSSmall membership function, due to the exponential ratio in data inputs [17; 23]. The overlay operator “AND” was utilized to combine all input variables by selecting the minimal values that are unique in different spaces based on a spherical semivariogram.

At landscape scale, the model was simulated through a step wise approach [17; 18] based on different periods of the year. The output of the model is an index for potential erosion ranging between 0 (low) and 1 (highest).

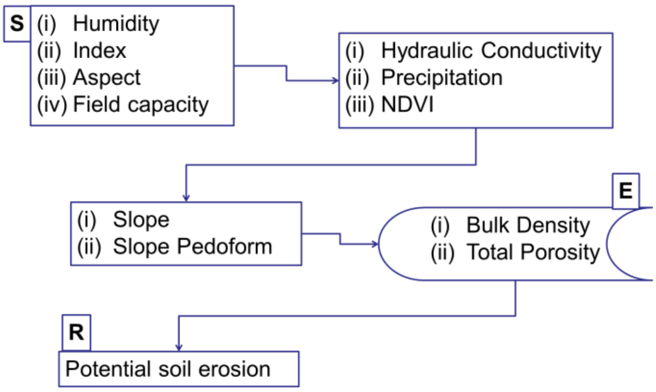

Figure 2. Modeling potential soil erosion: the FuDSEM model [2].

3.3 Data Processing

3.3.1 Soil Characteristics

The 24 point soil samples were dried, weighed and measured in the laboratory. The soil texture was used as input to compute for field capacity in the soil water characteristics model developed by the United States Department of Agriculture (USDA). The point data were then interpolated through spatial analysis in GIS, using ordinary Kriging and based on a spherical semivariogram, to provide a continuous raster surface for modelling. Characteristics of these soils are summarized in Figure 3.

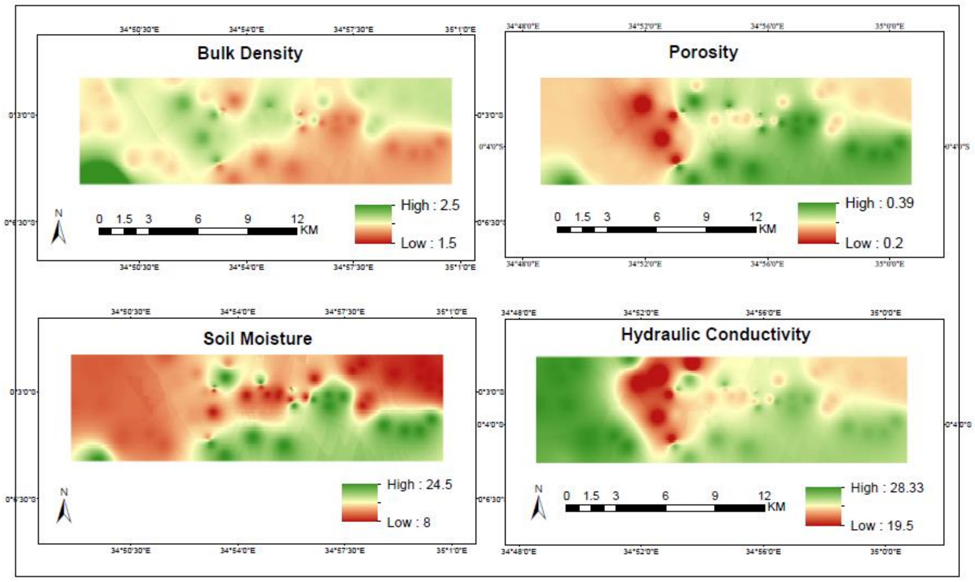

Figure 3: Soil physical properties for Kibos-Miwani sugar zone (August 2012)

3.3.2 Ground Survey Data

Collection of this data was aimed at describing Kibos land cover, crop species distribution and sugarcane management practices. Through cross tabulation, data collected showed a mixed cropping system with 76 % of the landscape covered with sugarcane which is planted in two planting seasons of March-April and September. 24% of the landscape was under subsistence crops, shrubs, fallow, and pasture land. About 87% of the sugarcane farmers burn sugarcane before manually slashing it, while 13% practice green cane harvesting.

3.3.3 Soil Erosion Model

We conducted three simulations with FuDSEM model, at different periods of the year. The selection of the periods was based on MODIS NDVI seasonal variations, and existence of clear Landsat5 images Landsat NDVI data for each of the simulation phase was used as the input of vegetation conditions at the time. All input data to the model are presented in Table 1.

Table 1. Summary of data inputs to the FuDSEM model simulations.

Input variable	Source	Acquisition date	Method
Bulk density	Ground survey	August 2012	Kriging
Humidity index	Soil moisture measurements	August 2012	Kriging
Hydraulic conductivity	Ground survey	August 2012	Kriging
Porosity	Ground survey	August 2012	Kriging
Field capacity	Texture measurements	August 2012	Kriging
Precipitation	KESREF database (rain-gauges)	2001-2012	Kriging
Slope	USGS DEM	2010	Computation
Curvature	USGS DEM	2010	Computation
Aspect	USGS DEM	2010	Computation
NDVI	Landsat5 images	2010/2011	Computation

4. RESULTS AND DISCUSSION

4.1 Temporal heterogeneity

MODIS 250 m NDVI exhibits two peaks (May and November) corresponding to the interaction between sugar-cane physiology and the bimodal rainfall with a one month time lag (Figure 4).

February indicates minimum vegetation while maximum vegetation is shown in May and November. We infer that rainfall distribution is the main driver of these variations. To calculate erosion risk for the three periods therefore, we selected three Landsat5 images corresponding to January (close to the minimum of vegetation development); June (close to the first maximum of vegetation development) and November (the second maximum of vegetation development).This selection was driven by the availability of cloud-free Landsat 5 images.

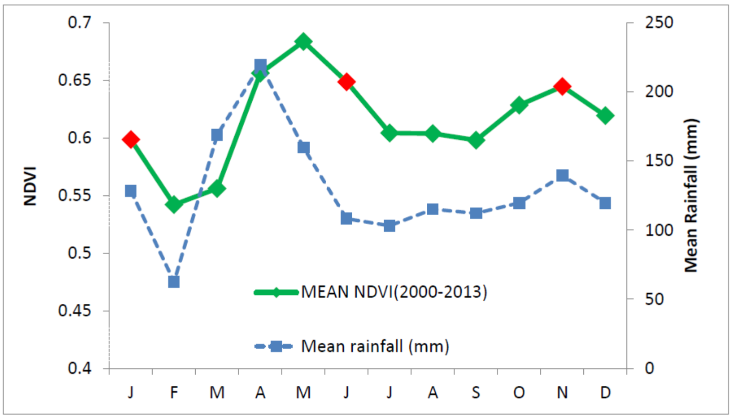

Figure 4. Mean monthly rainfall and mean seasonal vegetation conditions variability, as measured by MODIS, for the period 2000-2012 in Kibos. In red are months selected for FuDSEM simulations.

4.2 Spatial heterogeneity

The multiple planting harvesting dates and [9; 24] introduce heterogeneity between fields [25] within the same landscape (Figure 5). In their research, [2] concluded that heterogeneous landscapes influence rain drop intensity and rate of infiltration at different levels depending on type of vegetation. Landsat5 images have demonstrated spatial variability in vegetation conditions at the pixel (30 m) scale with vegetated, harvested and planted fields being identified on the image composite for the selected simulation periods. We infer that crop management is the main driver of these local variations.

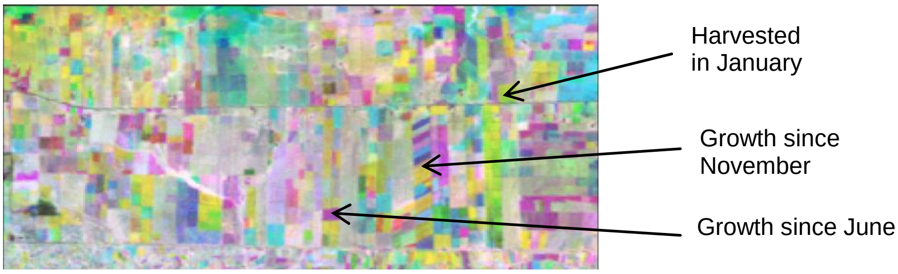

Figure 5. Landsat 5 NDVI colored composite image (R: January; G: June; B: November).

4.3 Potential Soil Erosion

Erosion risk values were simulated for January, June and November (Figure 6). The resultant erosion risk values range from 0.10 (green- lowest) to 0.75 (red-highest). There is homogeneous low erosion (in green color), in areas with natural land cover (shrubs and fallow) and a mosaic of medium to high erosion (orange to red) in the cropped area. Globally the mean value for erosion (0.42) does not change through time, with low slope sensitivity to erosion in the hilly landscape. November seems to be the period of less erosion in the cropped area (Circle 1 and 2). [2; 24] established that vegetation cover reduces rainfall intensity and runoff. We therefore infer that enhanced vegetation during the short rain season (November) minimized soil erosion. Observations on the 30 m pixels show moderate to intense erosion risk in cropped area (circles 1 and 2). There is variable risk of erosion from one pixel to the other in the three simulated months indicating that variability in vegetation conditions at the field scale (Figure 5) influenced soil conditions which eventually impact the erosion risk. We infer that crop management practices (planting and harvesting processes) are the drivers of erosion.

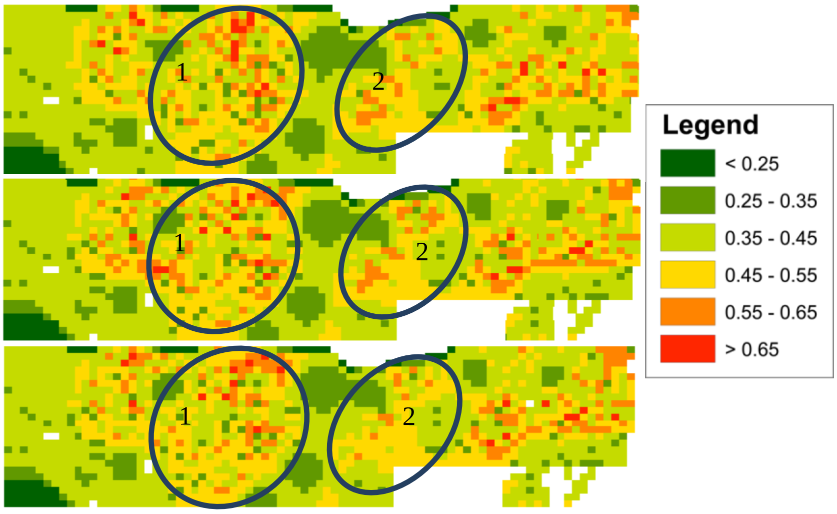

Figure 6: FuDSEM Erosion simulations for different vegetative seasons in Kibos – Miwani sugar zone.

5. CONCLUSION AND PERSPECTIVES

Satellite imagery has successfully characterized the spatial and temporal dynamics of Kibos-Miwani landscape by identifying relevant images to feed in the erosion model and partitioning the yearly physiological conditions of vegetation in the landscape. Rainfall has been found to be the main driver of temporal variations in NDVI at regional level. Images have further revealed the influence of cropping practices on risk of soil erosion. Results have shown low slope sensitivity to erosion risk during maximum vegetation periods. This is attributed to continuous sugarcane land cover in the landscape throughout the year that is able to interact with soil conditions to conserve soils from run off. Low erosion values have been witnessed in areas with natural land cover. We infer that the presence of vegetation in sugarcane cropping systems minimizes erosion risk. Moderate to intense erosion values have been noticed at pixel level, varying from one field to the other. This is attributed to cropping practices that include multiple planting and harvesting processes. We infer that crop management practices are the main drivers of erosion in a sugarcane landscape. These results are in agreement with [26] who realized that cropping practices which expose soils to rainfall posed a risk of soil erosion. As also observed by [27], we conclude that farmers living in similar landscapes should collaborate on soil and water conservation measures to minimize lose to soil erosion during their cropping activities for sustainable sugar cane production.

The next step will be to acquire a complete Landsat8 time series and collect ground data to improve erosion simulations by incorporating crop management practices (crop species and sugarcane harvesting process) at field scale, derived from satellite image analysis.

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